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Deprivation effects on length of stay and death of hospitalised COVID-19 patients in Greater Manchester

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Abstract

Introduction
The World Health Organisation declared a global pandemic in March 2020. The impact of COVID-19 has not been felt equally by all regions and sections of society. The extent to which socio-demographic and deprivation factors have adversely impacted on outcomes is of concern to those looking to 'level-up' and decrease widening health inequalities.

Objectives
In this paper we investigate the impact of deprivation on the outcomes for hospitalised COVID-19 patients in Greater Manchester during the first wave of the pandemic in the UK (30/12/19–2/1/21), controlling for proven risk factors from elsewhere in the literature.

Methods
We fitted Negative Binomial and logistic regression models to NHS administrative data to investigate death from COVID in hospital and length of stay for surviving patients in a sample of adult patients admitted within Greater Manchester (N = 10,372, spell admission start dates from 30/12/2019 to 02/01/2021 inclusive).

Results
Deprivation was associated with death risk for hospitalised patients but not with length of stay. Male sex, co-morbidities and older age was associated with higher death risk. Male sex and co-morbidities were associated with increased length of stay. Black and other ethnicities stayed longer in hospital than White and Asian patients. Period effects were detected in both models with death risk reducing over time, but the length of stay increasing.

Conclusion
Deprivation is important for death risk; however, the picture is complex, and the results of this analysis suggest that the reported COVID related mortality and deprivation linked reductions in life expectancy, may have occurred in the community, rather than in acute settings.

Highlights

- Older age and male sex are predictive of longer hospital stays and higher death risk for hospitalised cases in this analysis.
- Deprivation is associated with death risk but not length of stay for hospitalised patients.
- Ethnicity is associated with length of stay, but not with death risk.
- There is a social gradient in health, but these data would suggest that once in the care of an NHS hospital in an acute health episode, outcomes are more equal.

Keywords
COVID-19; inequality; administrative data; deprivation

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Introduction

Successive reviews of health inequality in the UK over the past forty years [1–4], have revealed a widening gap in health outcomes between the rich and the poor. Increasing deprivation is typically associated with poorer health outcomes [5–8]. The Marmot strategic review of Health Inequalities in England conducted in 2010 concluded that the social gradient in health identified first by Black [1], and subsequently by Acheson [2], persists in the UK and that reducing health inequalities is a matter of fairness and social justice. The report showed that people in the poorest areas on average had a life expectancy seven years below those living in the richest areas and for *healthy* life expectancy - the proportion of life lived without disability - the gap was seventeen years.

Since the first Marmot Review, progress in addressing health inequalities in England has been slow. A follow up report in 2020, showed that both improvements in life expectancy have stalled and that the social gradient of health has become even steeper. In some groups life expectancy has decreased in the past decade and the largest decreases have been in the most deprived areas, with a spatial element highlighting that deprived communities in the North have suffered disproportionately compared with wealthy areas of London. The gradient in healthy life expectancy has also worsened, with the most deprived areas experiencing more of their already shorter lives living with ill health [4].

Marmot and Allen [9] cite this lack of progress as a contributing factor to the poor state of health of the population of England immediately even before the declaration of a global pandemic in March 2020 [10]. Against this backdrop of growing health inequality, the burden of COVID-19 disease and mortality has also not been felt equally across the UK. Kontopantelis et al. [11] reported geographical and social patterns in excess mortality during the first wave of COVID-19 in the UK (February-July 2020) with excess mortality varying from 1 per 100,000 of population in Wales, to 26 in 100,000 in the West Midlands. In Greater Manchester, Marmot, et al. [12] reported that COVID-19 related mortality was 25% higher than that for England as a whole. Life expectancy in the city region is lower than the national average for England (GMHSCP 2015) and indeed this spatial inequality can be found *within* Greater Manchester [13]. For men, the difference in life expectancy between the most and least affluent wards is 18 years, and for women 13 years. This social gradient of life expectancy is mirrored in mortality from COVID-19 with Marmot, et al [12] reporting a stronger association between deprivation and mortality in Greater Manchester than other areas in England.

Background

Risk factors for severe and fatal COVID-19 infection

Evidence has emerged that there are multiple risk factors for severe and fatal COVID-19 infection. Older age groups are more at risk of hospitalisation and death from the disease, and men are more likely to be at an increased risk of severe infection [14, 15].

Drefahl et al. [16] linked recorded COVID-19 deaths in Sweden up to May 2020 to high quality personal records. Using individual level survival analysis, the authors showed that being male, having lower income and lower education levels all predict higher risk of death from COVID-19 even after controlling for the others. They conclude that the virus was, at that time, exerting an unequal burden on the most disadvantaged.

Williamson et al. [17] conducted a large cohort study of COVID-19 related deaths in England using primary care data (N = 17,278,392 patient records, N = 10,926 deaths). The authors found that male sex, greater age and deprivation to be associated with increased mortality. Underlying health conditions (diabetes, asthma and others) were also linked with increased mortality as was ethnicity, with black and South Asian people more likely to die. The study used only records from one provider of general practice electronic health record software and was conducted earlier in the pandemic. Period effects were not examined and there was a high level of missingness in the ethnicity characteristics of patients included (26%). The analysis did not include any measure of place.

Air pollution and COVID-19 have been linked in England at the regional level [18]. Controlling for age, population density and income, the authors showed positive association between the concentration of air pollutants (specifically nitrous oxides) and COVID-19 mortality. The study also demonstrated that $PM_{2.5}$ particulates were correlated with increased case numbers.

Length of stay

Evidence regarding the predictors of length of stay in hospital of COVID19 patients is mixed. Shryane et al. [19] investigated the length of stay of patients admitted to intensive care (ICU) between March and May 2020 using data from the COVID-19 hospital surveillance system (CHESS) in England. Changes in admission policy were found to be confounders of clinical knowledge of the disease in this early stage of the pandemic and the earliest admitted patients spent significantly longer in ICU than those admitted after April. Sex and ethnicity were not found to be related to the length of stay and there was a non-monotonic association with age (noting that the study also included patients who died in hospital which will have impacted the length of stay for older patients given their higher mortality risk).

Vekaria et al. [20] used four variables to predict length of stay for hospital admissions in a hospital in Manchester using different methods to model pathways to outcomes (discharge/death). In addition to sex and age, the authors found that the stage of the pandemic was predictive of the total length of stay, and that patients admitted to ICU who survive, have longer hospital stays.

Female sex, and kidney or liver disease were associated with longer lengths of stay in a retrospective cohort analysis of patients with COVID-19 in Hefei, China, in the earlier stage of the pandemic, excluding patients who died [21].

Research questions and motivation for this research

Given the literature cited above linking deprivation with poorer health outcomes, the documented excess mortality experienced by the population of Greater Manchester and the indications of within Manchester variation, there is a need for further research to explore the social gradient of COVID-19 health outcomes within GM and whether the nationally researched picture of the determinants of COVID-19 outcomes are relevant to the Greater Manchester context. The authors secured access to administrative hospital data for the GM population covering the course of the pandemic which provides us with a valuable opportunity to study this issue in depth. In this paper, we examine the effects of risk factors on the outcomes of hospitalised COVID-19 patients in Greater Manchester to assist in service planning as we transition to the disease becoming endemic, and to inform policy targeted at 'levelling up' between the most and least disadvantaged communities.

We address the following research questions:

1. Was deprivation associated with the risk of death from COVID-19 in Greater Manchester hospitals for patients admitted between 30/12/19 and 02/01/21?

2. Was deprivation associated with COVID death rates when measured at the local authority level for patients admitted to Greater Manchester hospitals between 30/12/19 January and 02/01/21?

3. Did deprivation predict the length of stay for cases of COVID-19 for patients admitted to Greater Manchester hospitals between 30/12/19 and 02/01/21?

To answer these questions, we use NHS administrative data to investigate severity of disease and death for patients hospitalised with COVID-19 in 2020 in Greater Manchester. We hypothesise that patients from more deprived areas who survived hospitalisation were more likely to spend longer in hospital, and that the risk of death would be associated with deprivation and other demographic factors. In Data and Methods we introduce the dataset used and the methods applied. Following this the results are presented and the findings discussed. Finally we appraise the strengths and weaknesses of the work and draw conclusions.

Data and methods

Secondary uses service data repository

The data are drawn from the Secondary Uses Service (SUS), a single repository for English healthcare data. The SUS data are the source for the hospital episode statistics (HES). When first produced the data quality is lower, however the data are cleaned over time and retrospective samples such as ours should be of the same quality as the equivalent HES data. The information collected for SUS is used by commissioners and providers of NHS care for non-clinical purposes including healthcare planning, service commissioning, tariff payment and policy development. Data Access was facilitated through the Greater Manchester Health and Social Care Partnership[1], the devolved body responsible for health and social care in the ten boroughs of the GM city region (see Figure 1). These data contain records of all hospital spells (admissions to a hospital). Each hospital spell is built from tables of hospital episodes (for example a move from intensive carte to standard ward would create a new episode). A single spell may relate to multiple hospital episodes for the same patient.

The data contain only completed spells and so any patients admitted during the study time frame who remained in hospital past 24/06/2021 (the end of the data made available for this work) are excluded.

We selected only those episodes for which the primary diagnosis code is related to COVID-19, i.e., where the primary diagnosis for the episode is either U071 or U072 in the ICD coding system (suspected or confirmed COVID- 19 illness)[2]. Where a unique patient ID re-occurred, the latest admission was selected, and earlier admissions excluded. The final dataset included N = 10,372 hospital spells. See Table 1 for the breakdown of spells by district The dataset creation path is shown in Figure 2 Descriptive statistics for the final sample are presented in section 3.5.

When a patient was readmitted for a further spell within the dataset time- frame, we selected only the latest spell relating to that unique ID; this removed 2361 (13.7%) of cases.[3]

To summarise, the inclusion criteria for the sample were in-patient spells which were:

1. for patients who were hospitalised within the Greater Manchester region between 30.12.2019 and 02.01.2021.

2. for patients who were registered with a general practitioner within Greater Manchester.

3. for patients who had a primary diagnosis of COVID-19 signified by diagnostic codes U072 or U071.

4. for patients aged 18 or over on admission.

5. the final spell of any patient admitted multiple times for COVID-19.

From this analytical sample of 10,372 spells, 3,268 resulted in a death. Of the surviving 7,104 patients, we are unable to determine if there were subsequent admissions for these patients during which they died, or if they died outside of

[1] https://www.gmhsc.org.uk/. Greater Manchester (GM) is the second biggest city region in the UK after London. It is divided into ten boroughs of which the City of Manchester is one. GM contains some areas of great affluence and others of strong deprivation; it is ethnically diverse. Although we could not claim that GM is representative of the UK, it does contain enough diversity to allow testing of the variables of interest.

[2] The data do not contain information on which variant of COVID the patient has so we were not able to include such information in our analyses. We discuss this issue in section 5.

[3] If we include all admissions, then we would be breaking the assumption of independent observations. Another alternative would have been to combine the admissions for each patient into a single record. However, this too was flawed as it made the effective assumption that the interim period outside of hospital was neutral and there are good reasons (the readmission) for assuming that this was an incorrect assumption. We acknowledge that the choice to only use the latest spell was also imperfect, but it was the least imperfect of all the choices as it avoided the structural censoring of the death outcome (if we had chosen an earlier spell).

Figure 1: Schematic map of greater Manchester's ten boroughs

Downloaded from: https://www.greatermanchester-ca.gov.uk/what-we-do/digital/get-online-greater-manchester/greater-manchester-wide-support/ 14th Jan 2024.

Table 1: Number of cases (spells) in study sample by local authority district

Local authority district	Number of spells
Bolton	1053
Bury	691
Manchester	1658
Oldham	1018
Rochdale	867
Salford	898
Stockport	1014
Tameside	1032
Trafford	786
Wigan	1355
Total	10372

hospital after their discharge from a spell within the data. This is a limitation of the SUS dataset - it contains only finished spells and so patients who are still in hospital who were admitted within the timeframe, do not appear in this analysis. Furthermore, it is not possible to identify cases in which COVID was acquired post hospitalisation, nor is it possible to detect cases (first or subsequent admissions) where the primary admission reason is for non-COVID related reasons, but there was also a COVID infection present.

For the length of stay models, we included all cases in the models. We included a dummy variable for whether the patient died during the spell (the 'death' variable) This balances the need to avoid selection biases whilst avoiding distorting model with an exogenous variable.

Outcome variables

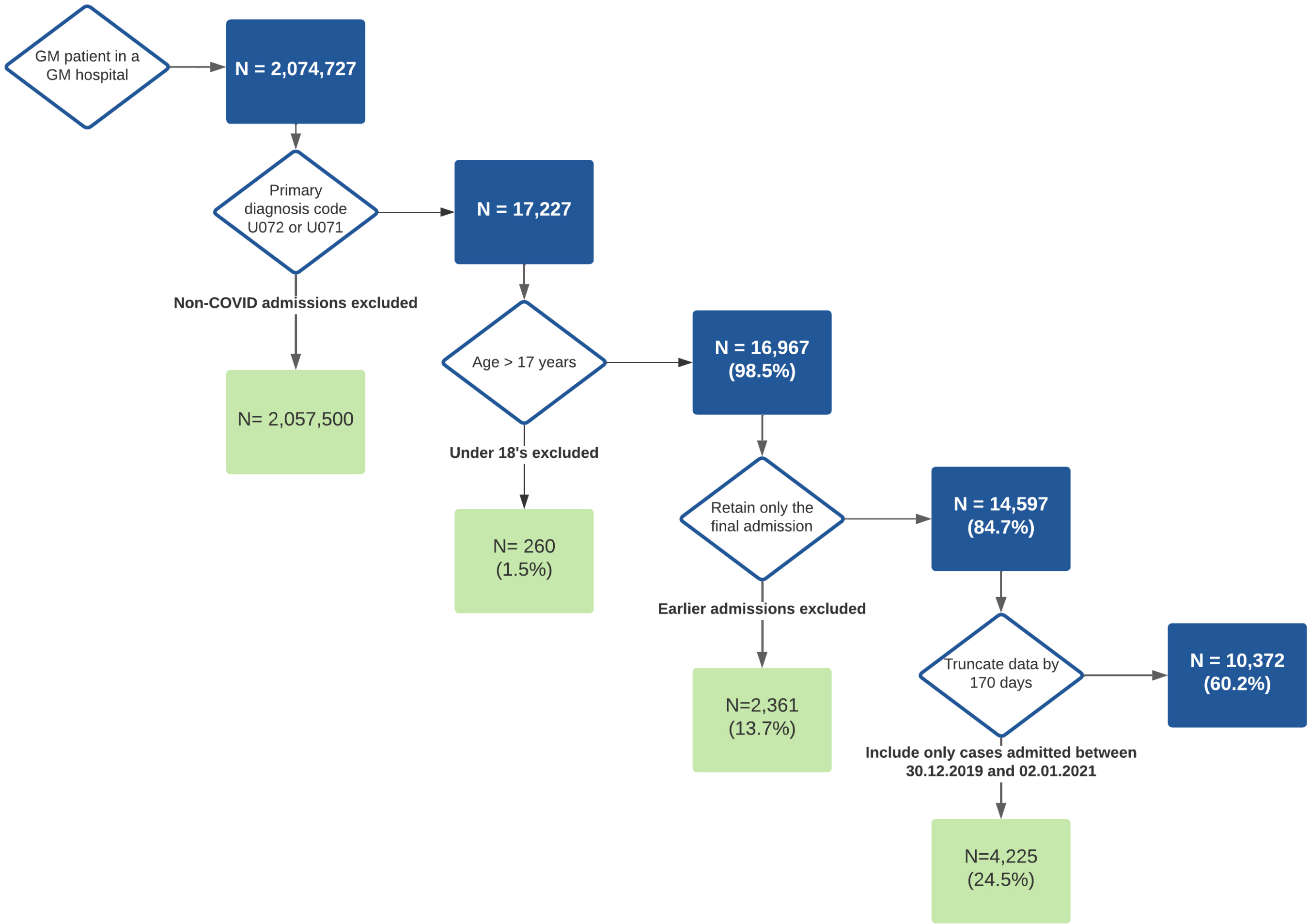
Death in these data is in fact all-cause mortality (i.e., death in hospital from any cause)[4] as we do not have the death certificates from which to select only patients for whom the cause of death is recorded as COVID-19. The patients selected into this analysis were all admitted with a primary cause of COVID-19 or suspected COVID-19 so we assume that for most patients this would also be the cause of death in the event of their dying in the hospital.[5] This is derived from a mode of discharge variable in the SUS data (for which death is one of the possible values).

Length of stay (LOS) is computed using the date difference between the admission and discharge dates for the spell. Zeroes were allowed as this is valid value (and the number of zeroes is a small proportion of the overall sample; 5.8%). Survival is determined from the discharge destination field within the SUS data. Patients discharged into any kind of

[4] In the paper, henceforth we will use the word "death" to mean "death in hospital from any cause after admission with a primary diagnosis of COVID-19".

[5] The criteria for inclusion as a covid hospitalisation required that one of two ICD codes relating to a covid diagnosis be listed as the primary admission code. This means that to the best of our knowledge and the capability of these data, the admission reason was for an acute covid. At the time of the work, there was some inconsistency in how deaths were recorded on death certificates and ultimately, the UK government moved to recording as COVID deaths as any death within 28 days of a positive test. The exact cause of death for each patient is thus somewhat unclear and so it is a working but reasonable assumption that those patients dying during a hospital spell for COVID-19 would have had COVID-19 recorded as the cause of death – of course some of these patients may have died *with* covid, rather than *of* covid, but this is not something we can extract from the data.

Figure 2: Flowchart of dataset sample selection



residential or home care are counted as surviving, and this date of discharge is considered to be the end of the hospital stay. We did not investigate subsequent deaths of patients hospitalised with COVID-19 as we do not have data on deaths outside the GMHSCP acute settings.

Covariates used in the analysis

In national level studies in the UK and elsewhere, age, sex and the week of admission (stage of the pandemic) have been shown to be important for length of stay [19–21]. Deprivation has been associated with increased COVID-19 mortality, as has ethnicity, age, underlying health conditions and sex [14–17]. Air quality has been associated with increased mortality [18]. Marmot, et al. [12] write that there are area differences in mortality in Greater Manchester and so for this reason, local authorities are included in the model for death. A timeline of relevant pandemic restrictions for Greater Manchester is included in Appendix A.

The variables used in the analysis have been selected based on existing literature and are detailed in Table 2. We compared Variance Inflation Factors and Pearson's Correlations for all variables and did not find any multi-collinearity.[6]

We included a variable to capture the timing of the admission, splitting the timeframe analysed into three distinct periods reflecting the changes in treatment protocols. Dummy variables for three periods to indicate when the admission occurred. Period 1 (the reference category) relates to all spells completed before 14/04/2020 (update of guidance on proning[7]). Period 2 relates to all spells completed after 14/04/2020 but before 16/06/2020 when Dexamethasone was approved [24]. Period 3 relates to spells completed after 16 June 2020. Spells are categorised into these periods by end date to capture the changes in treatment that a patient would have experienced. The guidance on proning and the approval of steroidal treatment for COVID-19 had a marked impact on death and recovery from the disease [25].

Modelling

We fitted a logistic regression model to the data to investigate the association between deprivation and death whilst controlling for known risk and demographic factors. Coefficient estimates, significance at the p<0.05 level, standard errors and 95% confidence intervals are presented in Tables 5 to 8.

To model length of stay we use a Poisson model as the data although theoretically continuous have the properties of a

[6] Defined as no Pearson's correlation of greater than 0.7 and no Variance Inflation Factor above 2

[7] 'Proning' refers to a medical intervention whereby a patient is turned to lie face down for a period of time to improve the efficacy of mechanical ventilation.

Table 2: Variables used in the analysis

Variable	Mean	Std Dev	Missing	Notes
Length of Stay (LOS)	10.90	14.50	0	Difference between the admission and discharge dates, in whole days. Descriptives are for patients who survived, N = 4,350. Source: SUS.
Died	0.32	–	0	Mode of discharge. 1 = died, 0 = survived. Source: SUS.
Deprivation	3.80	2.80	0	Index of Multiple Deprivation (IMD) decile for the respondent's LSOA as per registered address. A higher decile indicates lower deprivation. Source: English Indices of Multiple Deprivation [22]
Age	68.6	16.80	0	Age in years at the date of admission. Source: SUS.
Sex	0.44	–	0	Binary variable. 0 = Male, 1 = Female. Source: SUS.
Ethnicity	–	–	471	Ethnicity variable collapsed to four categories (White, Black, Asian, Other) due to small numbers. (Missing cases: 471) Source: SUS
Home air quality (AQ)	0.04	2.61	0	Index constructed by summing the standardised mean annual *NO2*, *SO2* and *PM10* scores in μ *gm3* for each LSOA. Source: AQ domains of the Access to Healthy Assets and Hazards Index [23].
Hospital site air quality (AQ)	0.71	2.86	0	As Home AQ but based on the site of the hospital. Source: AQ domains of the Access to Healthy Assets and Hazards Index [23].
Count of diagnoses	2.91	0.73	0	The natural log of the count of diagnoses is used as a proxy for co-morbidity. All cases had a minimum of 1 diagnosis and so there are no zero counts. Used as proxy for greater co-morbidities. The log of the count is used in this analysis. Source: SUS.
Timing of admission	–	–	0	Period 1 (reference) relates to all spells completed before 14/04/2020. Period 2 relates to all spells completed after 14/04/2020 but before 16/06/2020. Period 3 relates to spells completed after 16 June 2020.
Multiple admission	–	–	0	Indicator that the person has had at least one previous admission for COVID-19. Spells for patients have been subsequently readmitted within the data have been removed. 1 = final admission of multiple admissions for this patient, 0 = one admission only.
Local Authority	–	–	0	LA name (dummy variables), included in the model for death only.

count variable, we found overdispersion in exploratory Poisson models and so we fitted a Negative Binomial (NB) regression model to the data to account for this. The α parameter was estimated using an auxiliary ordinary least squares regression without a constant in line with [26].

For area effects, we modelled death rates of hospitalised patients at the Middle Super Output Area (MSOA) and Local Authority (LA) level using mean IMD deciles (aggregated from the lower super output area level), mean age from mid-year population estimates as of 2019, and the proportion male residents from mid-year population estimates as predictors. For the LA model, we were also able to include the proportion of Black, Asian and other ethnic minorities based on the 2011 census data.

For both death and length of stay models, the explanatory variables in denoted in Table 2 were included as covariates. They were then removed singly in reverse order of p-values until only significant coefficients remain. The reported models are these final models.

Truncation in the data

The data are structurally truncated. Only completed hospital spells are included within the dataset and so admissions at the end of the data period are likely to be omitted due to this truncation effect. This introduces a skew into the data, reducing the mean length of stay for later months. It is therefore important to conduct sensitivity analysis to enable use to make informed decisions regarding mitigating the impact this structural truncation on model estimates.

We conducted this sensitivity analysis by the following procedure. We removed cases admitted in the ten days prior to the last admission within the data. This we repeated at intervals of ten days. We observed that most parameter estimates were stable to this change in the data; however, the estimation of the period 3 effect was sensitive to the inclusion of later spells. Assessing the mean length of stay for the remaining data, we determined that the models and mean values stabilised after 170 days of removal as indicated by the

Figure 3: Length of stay by dataset size

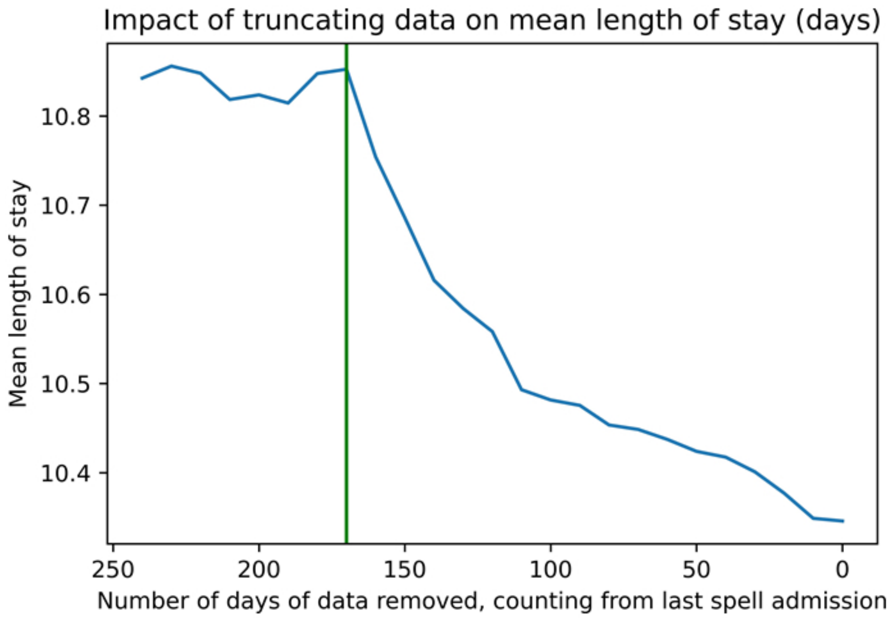
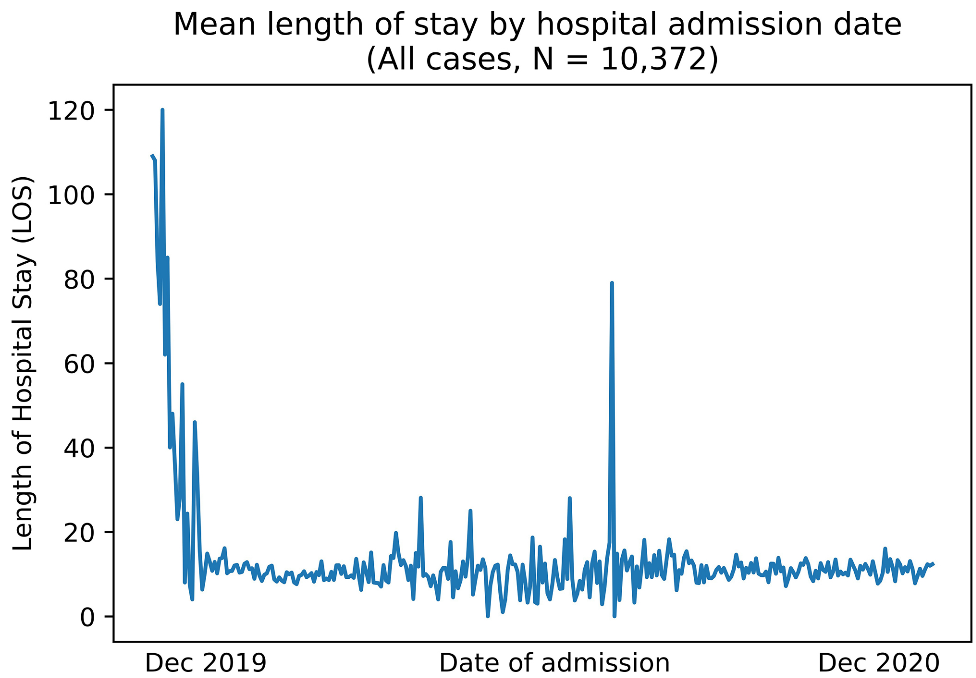


Figure 4: Length of stay by admission date



vertical line in Figure 3. The analysis therefore only includes spells admitted between 30/12/2019 and 02/01/2021. This has the additional benefit of removing the exogenous effect of vaccination on both length of stay and death. As we do not have vaccination status for individuals within the data, we are unable to control for this directly.

The length of stay is time dependent. For admissions early in the period, there were very low numbers with some long lengths of stay. The length of stay then became more stable as the number of cases increased - see Figure 4. The spike shown in these data relates to 25/08/2020. For this day, only two admissions are included in the dataset, one of which resulted in a length of stay of 79 days, the other 1 day. The mean length of stay for August admissions was 12.5 days and the mean number of admissions included per day was 5 admissions. This spike therefore represents the impact of an outlier in the data.

Results

Descriptive statistics and missing data

Low numbers necessitated the collapse of ethnic coding into four broad categories. Men outnumber women in the data across all ethnic groups as shown in Table 3.

Table 3: Sex by ethnicity. N = 10,372

Sex	White	Asian	Black	Other	Missing
Female	3,570	470	137	93	247
Male	4,397	679	203	142	434
Total	7,967	1,149	340	235	681

Table 4: Deaths by sex, N = 10,372

	Sex		
Died?	Male	Female	Total
No	3,872	3,232	7,104
Yes	1,983	1,285	3,268
Total	5,855	4,517	10,372

Table 5: Date of spell conclusion

Date of spell conclusion	Period	Number of spells
Before 14/04/2020	1	1,547
Between 14/04/2020 and 16/06/2020	2	2,651
After 16/06/2020	3	6,174

The mean age for men (68.1 years [std 16.0]) is lower than for women (69.1 years [std 18.0]). 33.8% of men died, compared with 28.4% of women (see Table 4). Of the 10,372 unique patients, 9,560 have only one recorded hospital spell in the dataset. 751 patients have two spells, and 61 patients have three or more spells. The death rate for spells which were the last in a series of more than one admission for a COVID-19 infection was lower (0.26) than for first admission spells (0.32). 6,174 (57%) of the spells concluded in period 3 (see Table 5).

Table 6: Length of stay by age category for survivors

Age range	Mean	Std dev	Count
Under 50	7.0	12.6	1,443
50-64	10.3	19.1	1,948
65-75	12.2	17.4	1,327
>75	13.6	13.0	2,386

The mean length of stay for was 10.9 days (std 14.5). The distribution of lengths of stay is shown in Figure 5 where 29 patients with stays over 100 days are removed for clarity; the maximum length of stay within the data is 321 days. This distribution includes the length of stay for patients who died in hospital.

Modelling risk of death

Table 7 shows the results of the logistic model for risk of death. Shryane et al. [19] identified a non-monotonic relationship between length of stay in the Intensive Care Unit and age. Using the same age banding categories as Shyrane et al. for comparison, the same effect does not appear to be present when considering total length of stay for survivors of a hospital spell (see Table 6). Age is associated with increased likelihood of death. We also tested age categories as dummy variables to assess non-linear and non-monotonic relationships and found none.

Figure 5: Distribution of length of stay, all cases, capped at 100 days for clarity (N = 10,337)

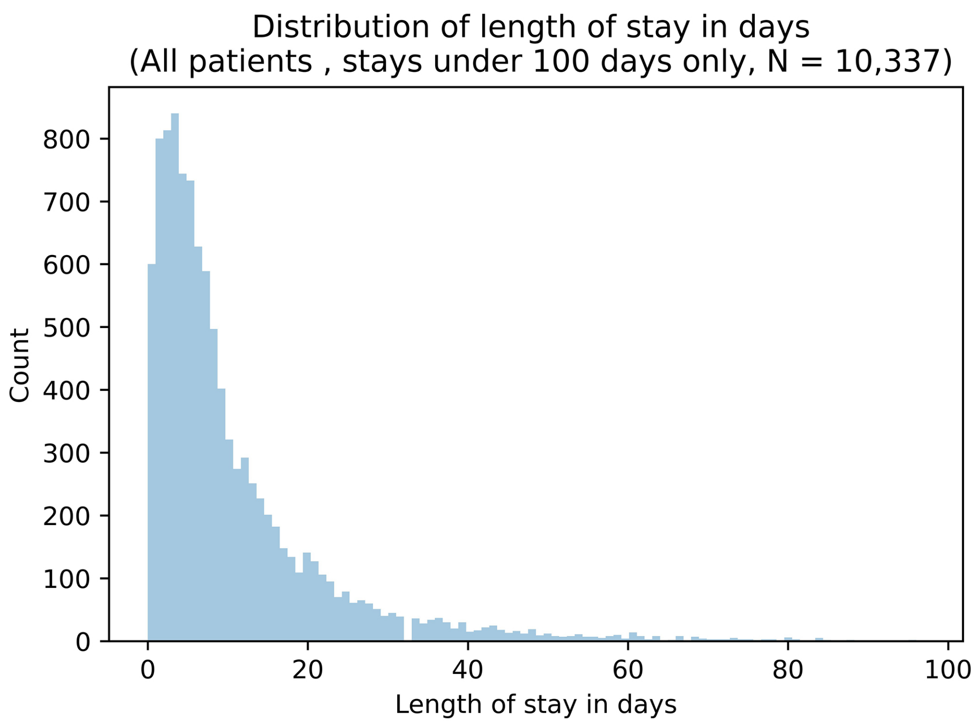


Table 7: Model 1: Logistic regression model for death. N = 10,372

	Coef.		Std Err.	95% Confidence interval	
				[0.025	0.975]
Intercept	−5.435	*	0.181	−5.789	−5.081
Multiple admissions	0.288	*	0.088	0.115	0.461
Sex	−0.395	*	0.047	−0.487	−0.302
Age	0.055	*	0.002	0.052	0.059
NumDiag Ln	0.394	*	0.036	0.324	0.464
IMD decile	−0.022	*	0.008	−0.039	−0.006
Period2	−0.563	*	0.074	−0.708	−0.418
Period3	−0.589	*	0.066	−0.718	−0.460

*Indicates significant at the p <0.05 level. AIC: 11,188, pseudo R2 = 0.140.

The parameter estimates of the model show that increased co-morbidity, age and male sex are associated with increased likelihood of dying. Spells ending in period 1 were more likely to result in death than 2 and 3.

Residing in a higher IMD decile (less deprived) was associated with a lower risk of death. Spells which were re-admissions for a COVID-19 infection, were less likely to result in death.

Air quality at either the home or provider site was not significant in the model for death, nor were the ethnicity dummy variables.

Model 1A (in Table 8) shows the impact of including local authorities as dummies within the model. Living in Bury, Wigan or Tameside was associated with increased death risk on hospitalisation compared with the reference category Manchester, the most deprived area. The measure of deprivation is significant; residing in a higher centile (less deprived area) is associated with decreased death risk.

The AIC value for model 1A is marginally lower than for Model 1. Other parameter estimates are not sensitive to the inclusion of the local authority and so we determine that there is evidence for place-based effects even after controlling for deprivation.

Modelling death rates at the local authority level

Table 9 shows the results of aggregate level modelling at the LA level for death risk, using an ordinary least squares approach. The model explains 64% of the variance in death rates between local authorities.

Local authorities with a higher mean IMD decile of the constituent LSOAs (i.e., composed of relatively less deprived geographical units in higher deciles) experienced a lower death rate for hospitalised patients when controlling for the mean age of residents. The proportion of resident males and ethnic make-up were not significant in this model.

Table 8: Model 1A: Logistic regression model for death including local authority names, N = 10,372

	Coef.		Std Err.	95% Confidence interval	
				[0.025	0.975]
Intercept	−5.526	*	0.186	−5.891	−5.160
Bolton	0.140		0.096	−0.049	0.329
Trafford	−0.122		0.115	−0.347	0.103
Wigan	0.410	*	0.089	0.235	0.584
Salford	−0.100		0.103	−0.302	0.102
Tameside	0.268	*	0.095	0.083	0.454
Oldham	0.073		0.098	−0.119	0.266
Stockport	−0.178		0.103	−0.380	0.023
Rochdale	0.195		0.101	−0.002	0.393
Bury	0.268	*	0.110	0.052	0.483
Multiple admission	0.293	*	0.089	0.119	0.467
Sex	−0.399	*	0.047	−0.491	−0.306
Age	0.055	*	0.002	0.051	0.059
NumDiag Ln	0.395	*	0.037	0.324	0.467
IMD decile	−0.019	*	0.009	−0.038	−0.001
period2	−0.590	*	0.075	−0.736	−0.444
period3	−0.629	*	0.066	−0.759	−0.499

*Indicates significance at the p <0.05 level. AIC: 11,139, pseudo $R^2 = 0.141$.

Table 9: Model 3: Ordinary least squares model for death rate in hospitalised patients at the Local Authority aggregate level, N = 10 authorities

	Coef.		Std Err.	95% Confidence interval	
				[0.025	0.975]
Intercept	−0.4687		0.234	−1.022	0.085
imd_dec_mean	−0.0389	*	0.013	−0.07	−0.008
mean_ages_LA	−0.0247	*	0.007	0.008	0.041

*Indicates significant at the $p < 0.05$ level, $R^2 = 0.642$.

Table 10: Model 2: Negative binomial regression model for length of hospital stay for all patients, N = 9,691

	Coef.		Std Err.	95% Confidence interval	
				[0.025	0.975]
Intercept	−0.5668	*	0.057	−0.678	−0.455
died	−0.1504	*	0.022	−0.193	−0.108
sex	−0.1273	*	0.019	−0.165	−0.09
age	0.0014	*	0.001	0.000	0.003
NumDiag Ln	0.7914	*	0.014	0.764	0.819
period2	0.5106	*	0.032	0.448	0.573
period3	0.5331	*	0.029	0.477	0.589
Asian	−0.0347		0.032	−0.097	0.028
Black	0.1706	*	0.054	0.065	0.276
Other	0.3109	*	0.064	0.185	0.437

*indicates significant at the $p < 0.05$ level, $\alpha = 0.79$.

We used the same approach to modelling death rates at the MSOA level, but parameter estimates were unstable using this smaller geographical unit.

Modelling length of stay

Table 10 shows parameter estimates for the negative binomial regression model for length of stay in hospital, considering all patients (model 2). Given the results of model 1 and 1A we tested the inclusion of local authority within the analysis. The inclusion of local authority destabilised the model estimates and no clear pattern of association emerges from their inclusion with very small effect sizes for any which do meet the significance criteria. We have therefore excluded these variables from this part of the analysis.

The key findings were:

- Age in single years is significant in this model, older patients have longer spells in hospital. Based on prior work in the area [19],we also tested age bands for a non-monotonic association with the length of stay (Under 50, aged 50-64, aged 65-74 and aged 75 and over) and found none.
- The length of stay was longer for patients in period 2 than period 1, but no longer again for those admitted during period 3.
- Being a member of some ethnic groups was associated with longer lengths of stay, Black and Other ethnic groups experienced longer lengths of stay compared with their White and Asian heritage counterparts. However, being of Asian heritage was not associated with longer lengths of stay compared with white ethnicity patients however[8].
- Co-morbidity was predictive of longer spell length.
- Deprivation, home air quality, provider site air quality and multiple admission were not associated with length of stay. We tested for non-monotonic effects in deprivation by including dummy variables for deprivation quintile but this also did not yield significant results.
- Provider site air quality was associated with longer stays where the index measure indicates poorer average air quality.

Sensitivity to model selection was tested by fitting Ordinary Least Squares and Poisson[9] models to the data. The variables identified as significant within Model 2 remained significant in the alternative approaches.

Discussion

Our study suggests that patients who were female in Greater Manchester were at lower mortality risk and had shorter hospital stays when infected with COVID-19. Age was also

[8] For cases where ethnicity was missing, we excluded the case from the analysis reducing the number of valid cases to N=9,691 (missing ethnicity variable = 861, 8.0%).

[9] We computed the likelihood ratio test statistic to compare Poisson and Negative Binomial models and confirmed that correcting for dispersion by using the Negative Binomial case gave a better fit to the data at the 0.001% confidence level.

another key risk factor with older age groups more likely to die from their COVID-19 infection.

The change in treatment protocols for COVID-19 was measured here by a marker for hospital discharge or death date. In both models, period effects are significant. Although there have been clinical studies into the effectiveness of different interventions, leading to evidence for their implementation, retrospective cohort studies have not (at the time writing) sought to control for period effects in this way, so the evidence here clarifies the pandemics progression. Death risk reduced as the pandemic progressed however length of stay increased. This may reflect a change in outcome for patients who with a similar level of disease in March might well have died, but who, when presenting a few months later, survived, albeit with a longer hospital stay on account of the severity of their disease. The alternative interpretation is that it was a capacity effect in period 1 where patients may have been sent home sooner than hospital norms and as the overall levels dropped then norms re-emerged seems unlikely as in Manchester although hospitals did fill up, the additional capacity Nightingale hospital was never actually used.

In this analysis, we segmented the time in hospital by key treatment change dates. Many other dates may have been relevant to treatment and disease progression. Although we can see clear period effects here associated with the dates chosen, we cannot necessarily link the specific changes in guidance to the improvement of outcomes using these data. The reduction in the risk of death with period, may also have reflected changes in other pandemic measures and population behaviours which shifted throughout the time of the study. Disease outcomes improved as the pandemic progressed in 2020 and this is likely linked to a better understanding of the nature of the virus and better experience of treating patients with severe disease.

Co-morbidity was important for death risk and for length of stay. Those patients with higher co-morbidity were more likely to die, and those who survived stay longer in hospital. Williamson et al. [17] showed an association between underlying health conditions and increased mortality risk from COVID-19, and Guo et al. [21] demonstrated a link between co-morbidity (specifically forms of kidney and liver disease) with longer lengths of stay for hospitalised COVID-19 patients. The results of our work are consistent with these previous studies and the results are consistent with patients who have underlying conditions being more likely to die, and more likely to develop severe disease requiring lengthy hospitalisation.

Multiple admissions were predictive of death, and this is to be expected; patients who have attended and been admitted to hospital multiple times for their COVID-19 infection are likely to be experiencing severe disease and they are therefore more likely to die. The multiple admission variable was not however associated with the length of stay in Model 2. It may appear surprising at first sight, but there is no reason a priori to expect the two response variables to have the same relationship with multiple admissions. Indeed, one might expect the relationship between multiple admissions and length of stay to be partially structural and/or affected by extraneous variables. It may be that the patients who are admitted multiple times present atypically and so appear well enough to be discharged but then deteriorate sufficiently for a readmission - potentially of differing lengths and severity at each time. It may also be that their home environment is not conducive to a rapid and secure recovery, leading them to be re-admitted. This 'bounce-back' pattern may therefore be too noisy to allow a clear signal to be distinguished in the data.

In the model for death, ethnicity does not feature, however Black and Other ethnic groups stayed longer in hospital than their White and Asian counterparts. Apea et al. [27] studied length of stay and outcomes for patients in East London and reported that adjusting for risk factors, Asian and Black heritage patients were more likely to die and had greater acute disease severity resulting in longer hospital stays. The work here demonstrates the same effect in for Black patients for length of stay only and the link between Asian ethnicity and more severe disease within the hospitalised population was not replicated in this Greater Manchester study. The same pattern of results was demonstrated by Alnababteh et al. [28]. Those authors retrospectively analysed adult patients in hospital in the same timeframe in the United States. Black patients' hospital length of stay was 21% longer compared with other ethnicities, but there was no difference found between ethnic groups for mortality. This replication of effects across contexts and healthcare systems is interesting and warrants further investigation.

Deprivation was not significant in the length of stay models, whereas it is significant in the model for mortality risk.

The proportion of deaths of hospitalised patients varies by local authority within the city region. For this dataset, only 61% of patients survived in Tameside where the mean IMD decile for the LSOAs within the authority is 3.6, versus 74% in Trafford with a mean IMD of 6.8. A model at the local authority level showed that deprivation within an LA is associated with the death rate for hospitalised residents, when controlling for the age of the LA population.

Male proportion and ethnic makeup were not statistically significant in this analysis but it is clear that there is a deprivation effect on the risk of dying in hospital from COVID-19, and that due to the spatial inequalities within Greater Manchester, some areas suffered a greater death rate than others. In a model at the MSOA level the same effect was observed, however a much smaller proportion of the variance was explained.

Using an area-based deprivation statistic for individuals has shown a link between mortality risk and deprivation and when aggregated based on geographical units, this effect persists. Purdam [13] showed spatial differences in life expectancy within the city region and in the review commissioned by the Greater Manchester Health and Social Care Partnership (GMHSCP) and Marmot et al [12] reported that there has been a significant change in life expectancy, correlated with deprivation-space in the Greater Manchester area; these effects are replicated in the individual level hospital data and so it seems that the acute care system is not able to cut through this unequal disease burden once hospitalised. This may be because of other risk factors we have been unable to capture (for example obesity, or specific forms of co-morbidity) or it may represent the long-term embedding of adverse outcomes associated with deprivation. Deaths occurring outside of the hospital system do not feature within this dataset and so we are unable to capture deaths either within private residences in the community or within the residential adult and elderly social care population. It is therefore likely that the death burden within the patients in this analysis is underestimated.

It may be the case that the predictors of the additional death burden replicate those identified in these non-hospitalised populations. We did not account for hospital overcrowding within the models which may have impacted admission decisions and could potentially have exacerbated area effects; however, we note that the 'Nightingale' hospital in Manchester was commissioned but remained unused, and therefore we assume that although the hospitals were very busy, they were not overwhelmed during the period of the study data.

Strengths and limitations

Previous analyses of length of stay have been restricted to the COVID-19 Hospital Episode Statistics (CHES) data, analysed in close to real-time for operational purposes. The CHES data is more limited and data quality improves with time as coding is updated and records quality checked meaning that analyses earlier in the pandemic were subject to significant truncation and missingness. The data used in this analysis include all hospitals within Greater Manchester and have the benefit of being temporally distant from the event which improves data quality and reduces the extent of missingness.

The data are truncated; the dataset contains only hospital spells which have completed by 24/06/21 and so any very long spells admitted before this date but not concluded are not included in the dataset. The first admission within the data is 30/12/19. We minimised this effect by selecting a defined period within the data availability, defined by sensitivity analysis to the truncation effect.

The time window of the study – admissions during 2020 – also means that we are focused here on the pre-vaccine period of the pandemic. This is both a strength and a limitation. The pre-vaccine response of the population to a pandemic is clearly an important subject of enquiry but this focus does mean that the findings may be less directly relevant to the current situation i.e., the post vaccine development of COVID-19 outcomes.

Delayed transfers of care are not accounted for in this model as the data were not available and so some longer stays may reflect a spell persisting because there is a difficulty in finding an appropriate discharge destination for a patient, rather than their ongoing care need being to stay in the acute setting.

We have no information on subsequent re-admissions after the dataset, or on deaths which occur post discharge in the community. There may also be deaths resulting from post COVID-19 infection complications which are coded as an admission for the primary presenting diagnosis and thus do not appear as a COVID-19 case in these data. For example, some patients have experienced cardiac health episodes, likely related to their prior COVID-19 infection, and these hospital episodes would not be recorded as a COVID-19 case but a death in this instance may well be related to the original COVID-19 infection.

The lack of data on deaths outside hospital is limitation of the study. This research was restricted to hospital data as it was conducted as part of an academic partnership, supporting the health board with operational research. It was not possible to link these data to external deaths. One option for extending this work would be to link the CHES data to other data sources – for example, the ONS deaths data which has the potential to improve the quality and richness of the analyses.

An assumption of the work reported here is that the model was uniform across areas with only changes to the intercept considered in model 1A. A further extension would be to test this assumption by fitting a multilevel model with random effects for local area and for period.

We note that Ethnicity and deprivation are likely to be associated both with each other intersectionally in terms of their effects on COVID outcomes and we did not consider that here, partly because of limitations of the size of the dataset leading to small counts in some intersectional cells. This is something which work on national datasets might want to consider.

One important topic to cover here is the issue of COVID variants. It is established that different COVID variants had different level of transmissibility, virulence and responsiveness to treatment (see for example [29, 30]).

All the cases in the UK were of the wild-type[10] until the Alpha variant emerged in late 2020. Alpha was concentrated in the southeast of England initially (it is sometimes referred to as the Kent variant); the Northwest – where Greater Manchester is located was one of the later affected regions with significant case numbers only starting to appear in the second half of December 2020; (see [31] for example). By the end of the study period, it was still not dominant in the Northwest, however, at least some of the cases in the period 3 data would likely have been Alpha.

Evidence is mixed on the virulence of Alpha compared to the wild-type. Some, e.g., [32] found no difference between alpha and wild-type for deaths in hospital, others e.g.,[33], show a higher death rate overall.

Data on which variant the patient had was not available to us within the dataset. We could in principle have imputed a probability that each case was alpha, based on the prevailing prevalence rates in the NW, However, this would have been a heuristic of dubious value and multicollinear with our period variable.

So, considering the lag between contracting the virus and hospital admission and lower rates of Alpha in the Northwest in the study period, the number of Alpha cases in our dataset is probably relatively modest. The likely impact on the findings of variants is minimal. Any effect is likely to have been a modest dampening of the period 3 coefficients in Tables 7, 8 and 10 but would not have altered the overall findings.

Conclusions

The results present a complex picture, and this is not easy to understand without further work. The widely reported link between deprivation and severe disease is detected for death risk for hospitalised patients within Greater Manchester but not for the length of stay. On the other hand, ethnicity is important for length of stay in the city region, but not for death risk upon hospitalisation.

[10] Wild-type covid refers to initial virus infections, prior to mutated 'variants' which emerged later in the pandemic.

A key point here is that the data only concern the hospitalised population so a key component of the data generating process for these data occurs after the event (infection) that drives the primary reason for the study. We need more research into how COVID-19 impacted different communities, with a broader range of data so we can understand how deprivation, ethnicity and space have intersected to impact on outcomes through the infection process.

Contribution

There have been many studies into the length of stay for COVID-19 patients, as medics seek to understand the patterns of disease for different patient groups and plan healthcare provision for their populations.

The current study used complete administrative data covering the whole of Greater Manchester for the period January - November 2020. The inclusion of more accurate and complete social, demographic and spell data for each stay has allowed a nuanced and detailed analysis of the factors affecting spell length and mortality in the city region for hospitalised patients.

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Statement on conflicts of interest

The authors have no conflicts of interest to declare.

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Appendix A: Abbreviated timeline of restrictions applying to greater manchester

Date	Details	National or local?
12/03/2020	Major sporting and cultural events suspended	National
17/03/2020	NHS cancellation of all non-emergency surgery	National
18/03/2020	All schools closed to students other than the children of 'key workers'	National
20/03/2020	Pubs, restaurants, cinemas, nightclubs, theatres, gyms and leisure centres closed	National
23/03/2020	National lockdown - citizens permitted to leave the home for a limited number of reasons only (food shopping, medical needs, essential work travel and to exercise once per day)	National
28/05.20	Groups of 6 permitted to meet up outside.	National
01/06/20	Reception, year 1 and year 6 allowed to return to school	National
30/07/20	Groups of 6 no longer allowed to meet up outside	Greater Manchester
14/9/20	Groups of 6 no longer allowed to gather	National
20/10/20	Tier 3 restrictions imposed	Greater Manchester
31/10/20	Second national lockdown imposed	National
19/12/20	Tier 4 restrictions imposed in the south of England, all other lifting of restrictions cancelled and restricted to Christmas day only	National